



User Guide for Discrete Adjoint Solver in TAU

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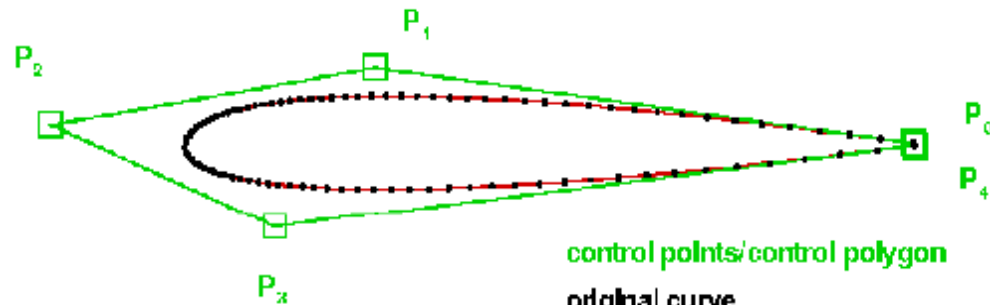
Content

- **Motivation of adjoint approach by optimization problem**
- **The adjoint (or dual) equation**
- **The adjoint approach**
- **Discrete adjoint solver in TAU (PETSc / FaceMat)**
- **Installation of TAU for PETSc use**
- **Input parameters / Settings**
- **1. Tutorial / Exercise**
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- **2. Tutorial / Exercise**
- **3. Example (Optional)**

NOTE: All mentioned files and documents are part of the delivered tar archive



Aerodynamic Shape Optimization



Parameterized
airfoil

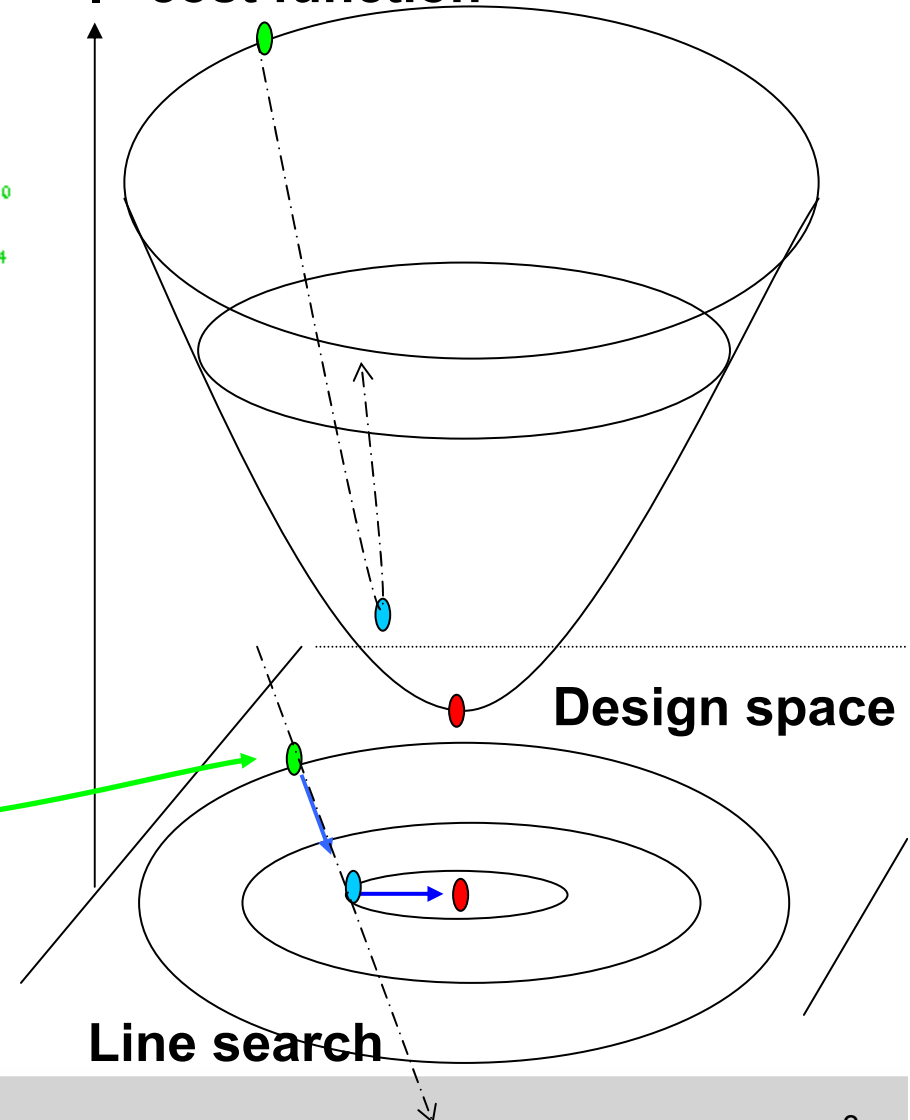
Vector of (design)
parameters P

Search direction

“ : $-\nabla I = -\left(\dots, \frac{\delta I}{\delta P_i}, \dots \right)_{i=1, \dots, n}^T$ “



I cost function



Finite Differences

i-loop
i=1,...,n

Variation of i-th design variable

$$\delta C_D = \frac{2}{\gamma M_\infty^2 p_\infty C_{ref}} \int_C \delta p (n_x \cos \alpha + n_y \sin \alpha) dl$$

$$+ \frac{1}{C_{ref}} \int_C C_p (\delta n_x \cos \alpha + \delta n_y \sin \alpha) dl ,$$

Metric sensitivities → **pressure variation** → **aerodynamic sensitivity**

i-th component of cost function's gradient

• **Finite Differences**



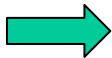
**n design variables require
n+1 flow calculations**






Motivation of Adjoint Approach

High number of design variables

• Finite Differences  n design variables require
n+1 flow calculations

• Adjoint Approach  n design variables require
1 flow and
1 adjoint flow calculation

**Independent of number of
design variables**

High accuracy



Adjoint Calculus via Lagrangian Function

Optimization problem: $\min_P I(U(P)) \quad s.t. \quad R(U(P)) = 0$

Lagrangian function: $L(U, \psi, P) := I(U(P)) + \psi^T R(U(P))$

The Lagrangian multiplier ψ becomes vector of adjoint (or dual) variables for stationary points

Stationary points need to fulfill necessary optimality condition (KKT):

$$\overset{!}{\nabla L} = 0, \quad i.e. \quad \frac{dL}{d(\psi, U, P)} = 0, \quad \Leftrightarrow \quad \frac{dL}{d\psi} = R(U) = 0 \quad (\text{state eq.})$$

$$\text{and} \quad \frac{dL}{dU} = \frac{\partial I}{\partial U} + \psi^T \frac{\partial R}{\partial U} = 0 \quad (\text{dual or adjoint eq.})$$

$$\text{and} \quad \frac{dL}{dP} = \frac{dI}{dP} = \frac{\partial I}{\partial P} + \psi^T \frac{\partial R}{\partial P} = 0 \quad (\text{design eq.})$$

Adjoint Approach for Sensitivities / Gradients

Solve flow Problem:

$$R(U) = 0$$

Build up adjoint equation and solve for ψ : $\frac{\partial I}{\partial U} + \psi^T \frac{\partial R}{\partial U} = 0$

Use one and the same adjoint solution ψ to calculate the sensitivities / gradient via:

$$\frac{dI}{dP} = \frac{\partial I}{\partial P} + \psi^T \frac{\partial R}{\partial P}$$

Note: We only need to determine the partial derivatives w.r.t. the vector of (design) parameters P

There are different ways to calculate the partial derivatives:

$$\frac{dI}{dP} = \frac{\partial I}{\partial P} + \psi^T \frac{\partial R}{\partial P}$$

How to calculate the partials?

There are different ways to calculate the partial derivatives:

$$\frac{dI}{dP} = \frac{\partial I}{\partial P} + \psi^T \frac{\partial R}{\partial P}$$

easy to evaluate,
direct calc. by (adj.) solver

here we have two
possibilities, see below

First approach: Direct calculation by the (adjoint) solver

→ available for $\alpha, \beta, Ma, \rho_\infty, T_\infty$ (see details later on)

Second approach: The „volgrad“ method

→ solve for $R(U) = 0$, then perturb P (component by component)
and measure the defect in the residual – this defect is the partial
derivative $\frac{dR}{dP}$



How to build up the adjoint equation?

There are two paths to build up and solve the adjoint equation $\frac{\partial I}{\partial U} + \psi^T \frac{\partial R}{\partial U} = 0$:

- Build up Jacobians and solve adjoint equation by **PETSc**
 - Visit PETSc Homepage: <http://www.mcs.anl.gov/petsc/petsc-as/>
 - Most accurate way to build up Jacobians
 - Capable to build up derivatives w.r.t. SA, SAE, Wilcox k-w turbulence models
 - Efficient adjoint solve, but memory consuming
 - Sequential only
 - Recommended for 2D cases
- Build up Jacobians and solve adjoint equation by **FaceMat** option
 - Only frozen turbulence and TSL
 - Efficient w.r.t. memory, but more expensive w.r.t. run time
 - Parallel option
 - Recommended for 3D cases

→ See next slide for further details

Discrete Adjoint Solver in TAU

Jacobian

Parameters: from spatial discretization

Both Jacobians:
Turb: 1st-order turb, SA, SAE, Wilcox k-w
BCs: Wall, ffield (no vortex corr), sym

~14x memory
seq only

PETSc
 Central/upwind,
 full visc, diss
 coeff, lam visc

„FaceMat“
 Central scalar,
 TSL visc

~4x memory
parallel

Set up Adjoint
equation system

Solve the Adjoint
equation system

Solution

Parameters: from iterative method, CFL nr etc.

5% solution
time
 Turb prob
requires
 ILU(n) $n \gg 1$

PETSc
 ILU(n)
 GMRes, BiCGStab
 Direct LU factor

Classic
 GMG
 RK/LU-SGS
 GMRes

150% solution
time
 Can't solve turb
prob

Both Methods:
 Parallel

**Development, verification
 & very efficient 2d
 (Sequential only)**

**„Production“
 Version (3d)
 (Parallel)**





Installation

- Installing TAU will only give you FaceMat, i.e. frozen turb.
- To use PETSc:
 - First install PETSc libraries
 - See guide [Compiling_TAU_with_PETSc.pdf](#) to install TAU with PETSc
 - Update your `.taudef` file to include PETSc path
 - Recompile TAU
 - Change „Linear residual type“ from default „Facemat“ to „PETSc“ in input file (details later on)
 - Change „Jacobian frozen turbulence (0/1)“ (details later on)
- **Note:** Not possible to install TAU with PETSc and Python!



Input Parameters / Settings for Discrete Adjoint Solver in TAU

Set Solver type: to DAdjoint for discrete adjoint solver in TAU

For Linear residual type: choose Facemat or PETSc

For PETSc choose Relaxation solver: PETSc

NEVER(!) use parallel option or multigrid with PETSc options!

ONLY(!) use Central convective turbulence flux: Roe with PETSc

Choose your Cost function: as C-drag, C-lift or C-my

**(Only) For direct computation of partial derivatives (instead of “volgrad”)
choose Design variable: (e.g. Farfield-alpha)**





Input Parameters / Settings for Discrete Adjoint Solver in TAU

With Facemat choose only(!) 0 (never(!) 1) within the following block:

```
Jacobian variables: Cons
Jacobian constant laminar viscosity (0/1): 0
Jacobian frozen turbulence (0/1): 0
Jacobian constant dissipation coeffs (0/1): 0
Jacobian volume scaling (0/1): 0
Jacobian includes timestep (0/1): 0
Jacobian turb. includes timestep (0/1): 0
```

Reason: Facemat bases already on certain simplifications (e.g. frozen turbulence)

0 means off, 1 means on

Now we explain the input parameters of the above given block line by line ...





Input Parameters / Settings for Discrete Adjoint Solver in TAU

For PETSc options you can choose ...

Jacobian variables: Cons

Usually one takes Cons, i.e. conservative variables are chosen instead of primitive ones (recommended!)

Jacobian constant laminar viscosity (0/1):

When constructing the Jacobian make the simplifying assumption that the laminar viscosity is constant w.r.t. the linearization

Jacobian frozen turbulence (0/1):

Stronger than the above assumption; equivalent to the assumption in Facemat

Jacobian constant dissipation coeffs (0/1):

Assumption: Coefficients of central dissipation are constant w.r.t. linearization





Input Parameters / Settings for Discrete Adjoint Solver in TAU

For PETSc options you can choose ...

Jacobian volume scaling (0/1):

Scale the rows of Jacobian by local cell volume (may improve conditioning of the linear system)

Jacobian includes timestep (0/1):

Makes a contribution of the reciprocal of the timestep (CFL number based) to the diagonal entries of the Jacobian

Jacobian turb. includes timestep (0/1):

As above, but only for turbulence equations

Note: The most accurate way is to choose PETSc with 0 for the whole block (recommended!)





Input Parameters / Settings for Discrete Adjoint Solver in TAU

IMPORTANT(!): For use of PETSc you have to add the following line in your parameter file:

PETSc options: `-pc_type ilu -pc_factor_levels 4 -ksp_type gmres -ksp_max_it 200 -ksp_rtol 1.e-12 -ksp_monitor`

It is highly recommended not to change this options!

For further details see TAU User Guide [user_guide.pdf](#)

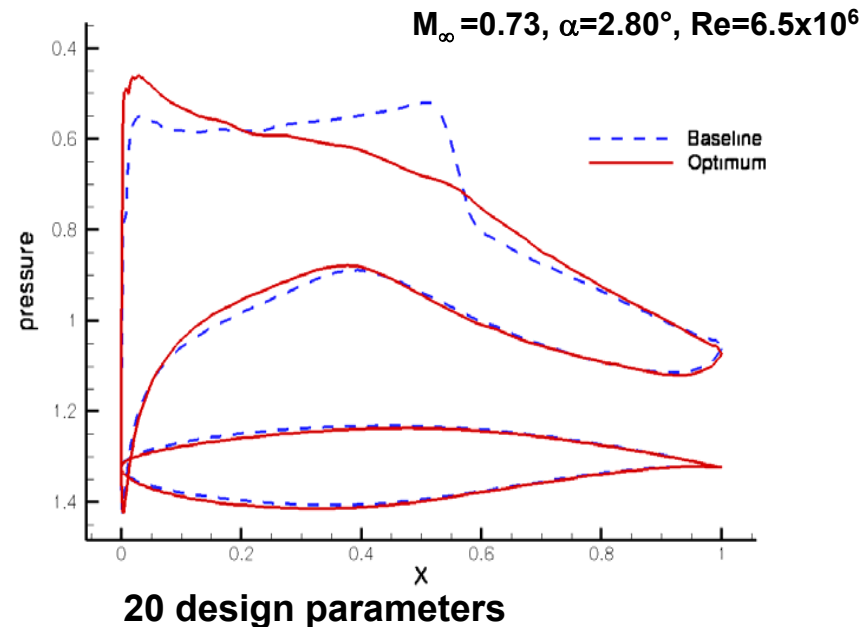
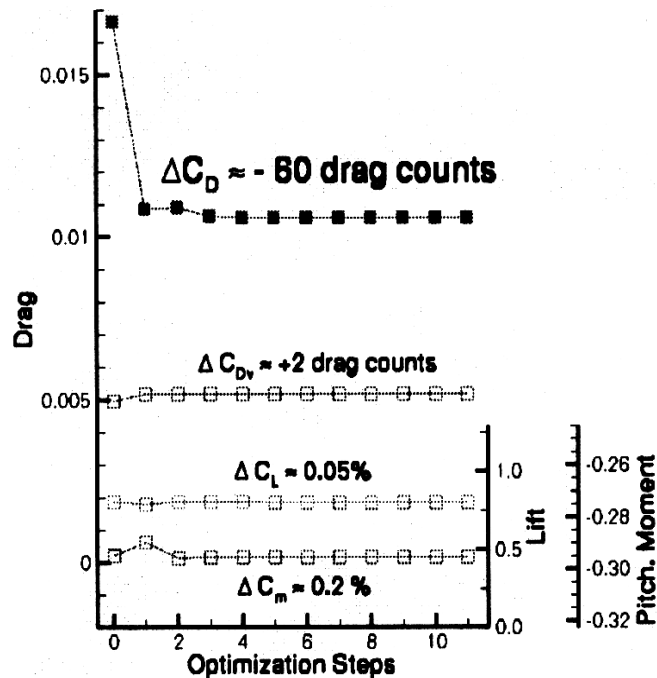
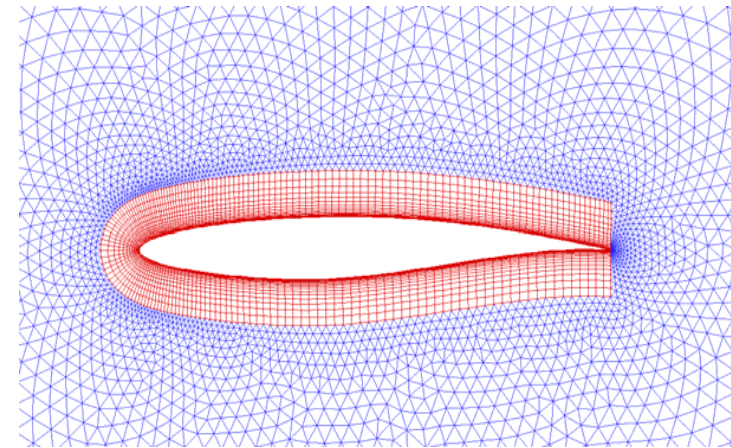
and <http://www.mcs.anl.gov/petsc/petsc-as/>



Example: Shape Optimization Based on Discrete Adjoint

Objective

- drag minimization for RAE 2822 airfoil at constant lift, pitching moment and AoA
- projected steepest descent strategy
- flow solver: viscous TAU-Code, SA model
- adjoint solver: viscous discret TAU adjoint





1. Example / Tutorial

Adjoint version of Case 9:

The example including grid, parameter files and instructions (README) you will find in the file /1_RAE2822_petsc_kw/

You will learn how to solve $\frac{dC_L}{d\alpha}$ via (discrete) adjoint simulation, using PETSc and Volgrad

Just follow the instructions in the README file ...

Later on you can repeat everything with appropriate settings for Facemat option

Have fun and success ;-)



Dual (Adjoint) Weighted Residual Approach (DWR)

h Fine mesh

H Coarse mesh

U_h^H State variable U extrapolated from coarse to fine mesh

It holds: $R_h(U_h) = 0$

Then usually we have: $R_h(U_h^H) \neq 0$

In the following, we explain the approach of **Dual Weighted Residuals (DWR)** for error estimation (in FV context):

➤ (DWR for FEM: [Rannacher et al., 1997])

➤ DWR for FV: [Venditti and Darmofal, 2002]:

Dual (Adjoint) Weighted Residual Approach (DWR)

Taylor-series expansion of cost function and residual:

$$I_h(U_h) = I_h(U_h^H) + \frac{\partial I_h}{\partial U_h} \bigg|_{U_h^H} (U_h - U_h^H) + \dots \quad (1)$$

$$R_h(U_h) = R_h(U_h^H) + \frac{\partial R_h}{\partial U_h} \bigg|_{U_h^H} (U_h - U_h^H) + \dots \quad (2)$$

We convert eq. (2) and restrict to 1. order terms:

$$\left(\frac{\partial R_h}{\partial U_h} \bigg|_{U_h^H} \right)^{-1} (R_h(U_h) - R_h(U_h^H)) \approx (U_h - U_h^H) \quad (3)$$

= 0

Substitution of eq. (3) in (1) yields:

$$I_h(U_h) \approx I_h(U_h^H) - \frac{\partial I_h}{\partial U_h} \bigg|_{U_h^H} \left(\frac{\partial R_h}{\partial U_h} \bigg|_{U_h^H} \right)^{-1} R_h(U_h^H) \quad (4)$$

Dual (Adjoint) Weighted Residual Approach (DWR)

It holds:

$$I_h(U_h) \approx I_h(U_h^H) - \frac{\partial I_h}{\partial U_h} \bigg|_{U_h^H} \left(\frac{\partial R_h}{\partial U_h} \bigg|_{U_h^H} \right)^{-1} R_h(U_h^H) \quad (4)$$

The adjoint equation reads: $\frac{\partial I}{\partial U} - \psi^T \frac{\partial R}{\partial U} = 0$

Consequently, we have: $\left(\psi_h \big|_{U_h^H} \right)^T = \frac{\partial I_h}{\partial U_h} \bigg|_{U_h^H} \left(\frac{\partial R_h}{\partial U_h} \bigg|_{U_h^H} \right)^{-1} \quad (5)$

Finally, substitution of eq. (5) in (4) yields:

$$I_h(U_h) \approx I_h(U_h^H) - \left(\psi_h \big|_{U_h^H} \right)^T R_h(U_h^H) \quad (6)$$



Dual (Adjoint) Weighted Residual Approach (DWR)

It holds:

$$I_h(U_h) \approx I_h(U_h^H) - \left(\psi_h|_{U_h^H} \right)^T R_h(U_h^H) \quad (6)$$

We do the further approximation

$$\psi_h|_{U_h^H} \approx \psi_h^H$$

and finally we get the **error estimate** by Venditti and Darmofal

$$I_h(U_h^H) - I_h(U_h) \approx \underline{\left(\psi_h^H \right)^T R_h(U_h^H)}$$

Dual weighted residual (DWR)



Dual (Adjoint) Weighted Residual Approach (DWR)

It turns out, that the repeated extrapolation between certain mesh levels in practice is not handy.

Therefore, instead of $I_h(U_h^H) - I_h(U_h) \approx \left(\psi_h^H\right)^T R_h(U_h^H)$,

we consider $I(U_h) - I(U) \approx \psi_h^T R(U_h)$.

Now the idea (by R. Dwight) is, to interpret the discretization error $R(U_h)$ as dissipation error. This yields:

$$I(U_h) - I(U) \approx \psi_h^T \left(k^{(2)} \frac{\partial R}{\partial k^{(2)}} + k^{(4)} \frac{\partial R}{\partial k^{(4)}} \right)$$



Dual (Adjoint) Weighted Residual Approach (DWR)

The (global) value

$$\psi^T \left(k^{(2)} \frac{\partial R}{\partial k^{(2)}} + k^{(4)} \frac{\partial R}{\partial k^{(4)}} \right),$$

is a scalar product over the computational mesh, i.e. we have a summation over all mesh cells of terms

$$\psi_{i,j}^T \left(k_{i,j}^{(2)} \frac{\partial R_{i,j}}{\partial k^{(2)}} + k_{i,j}^{(4)} \frac{\partial R_{i,j}}{\partial k^{(4)}} \right).$$



Sensor for mesh adaptation
(Local dual weighted residual)

Input Parameters / Settings for Discrete Adjoint Solver in TAU

For adjoint-based error estimation we have the following additional parameters:

Set Solve dissipation error equation (0/1) : **to** 1:

This means we assume $R_{i,j}(U_h) \approx k_{i,j}^{(2)} \frac{\partial R_{i,j}}{\partial k^{(2)}} + k_{i,j}^{(4)} \frac{\partial R_{i,j}}{\partial k^{(4)}}$

Note: The original approach of Venditti and Darmofal is not supported in TAU!

Set Solve linear problem on grid level: **to** appropriate number

Note: The field output V4 is (dependent on cost function):

$$\text{abs} \left[\psi_{i,j}^T \left(k_{i,j}^{(2)} \frac{\partial R_{i,j}}{\partial k^{(2)}} + k_{i,j}^{(4)} \frac{\partial R_{i,j}}{\partial k^{(4)}} \right) \right]$$



(Local) Adjoint-based Error Estimate / Sensor for Mesh Adaptation by DWR

Field output V4, dependent on
cost function

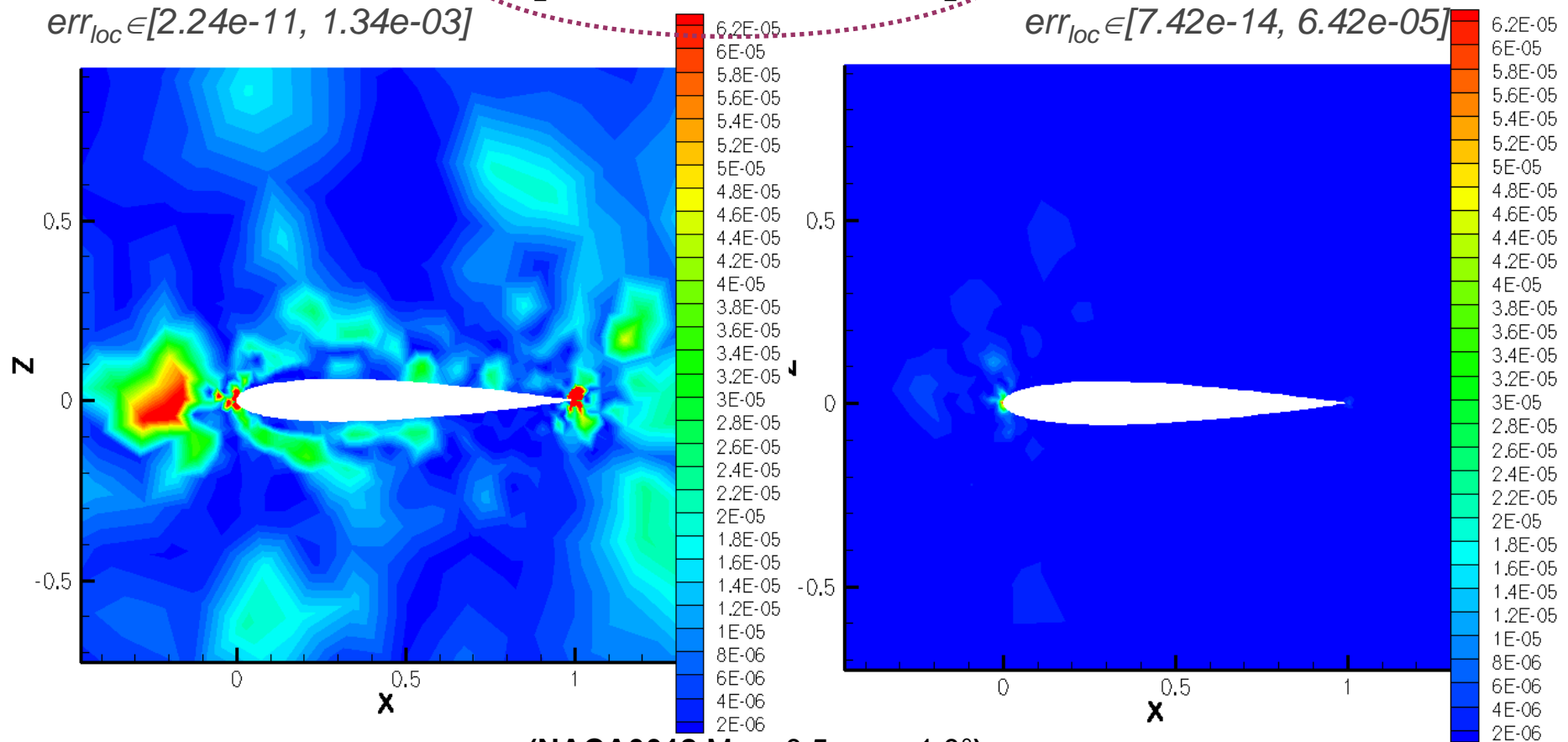
Lift

$err_{loc} \in [2.24e-11, 1.34e-03]$

$$abs \left[\psi_{i,j}^T \left(k_{i,j}^{(2)} \frac{\partial R_{i,j}}{\partial k^{(2)}} + k_{i,j}^{(4)} \frac{\partial R_{i,j}}{\partial k^{(4)}} \right) \right]$$

Drag

$err_{loc} \in [7.42e-14, 6.42e-05]$



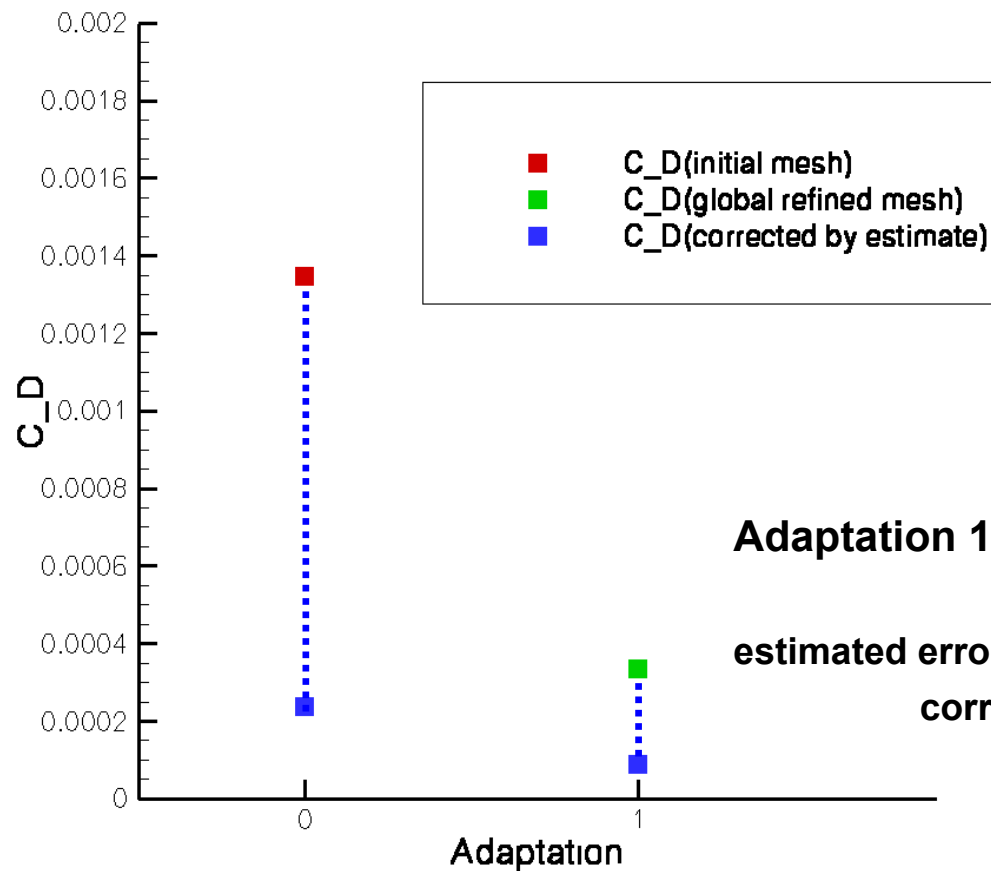
(NACA0012 Ma = 0.5, $\alpha = 1.0^\circ$)



Adjoint-based (Global) Error Estimate and Correction

NACA0012 (Euler flow)

Ma = 0.5, $\alpha = 1.0^\circ$

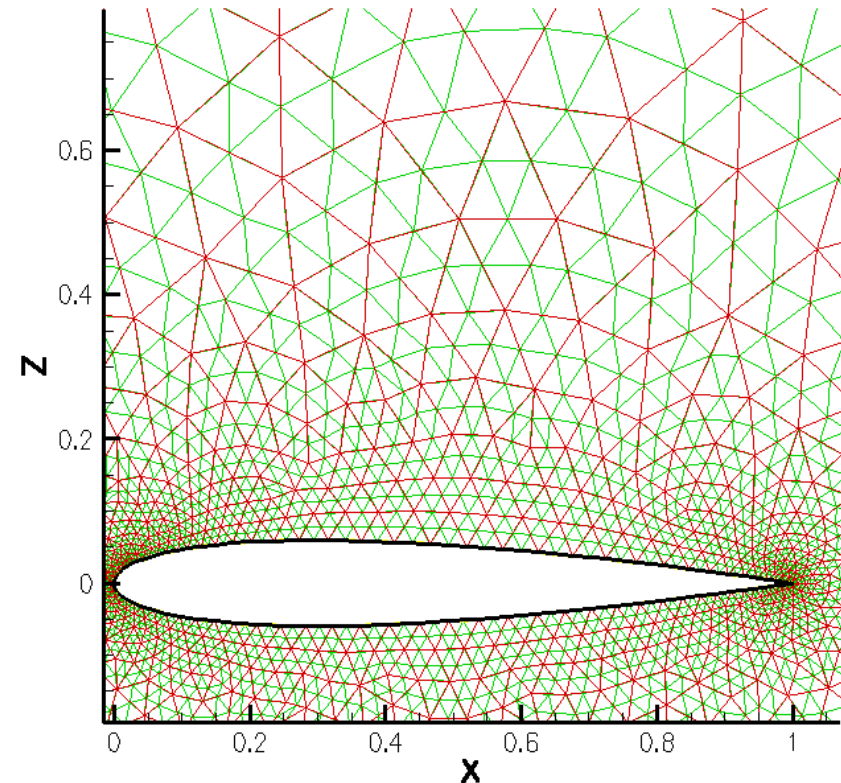


Adaptation 1:

C_D (global refined mesh) = 0.00033382

estimated error = $\Psi^*[(dRdk2 * k2) + (dRdk4 * k4)] = -0.00024721$

corrected C_D for global refined mesh = 0.00008661





2. Example / Tutorial

NACA0012 (inviscid):

The example including grid, parameter file and instructions (README) you will find in the file /2_NACA0012_err_estimate/

You will learn how to calculate global error estimates.

Just follow the instructions in the README file ...

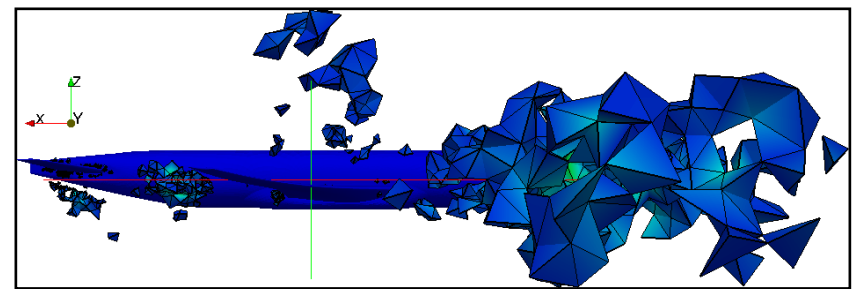
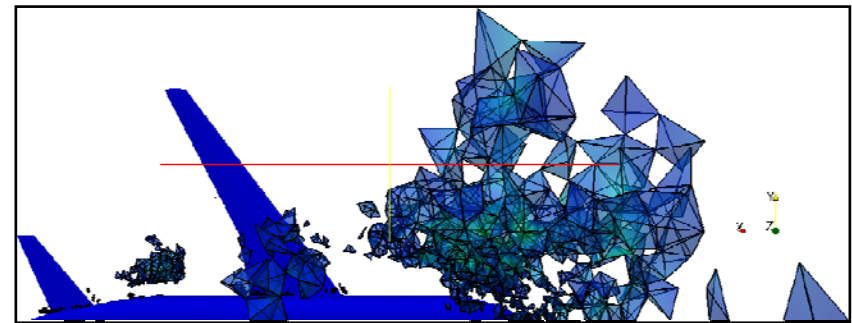
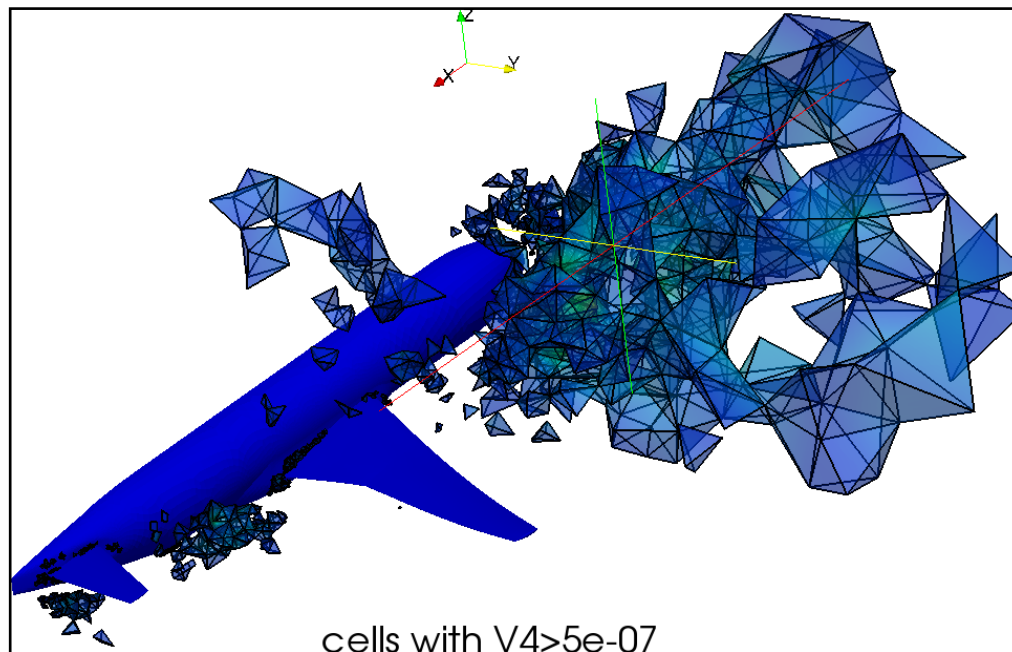
In addition, you learn how to calculate $\frac{dC_D}{d\alpha}$ different from the “volrag way”.

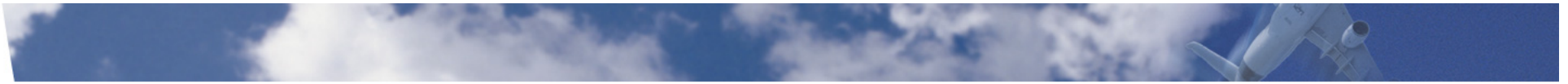
Have fun and success ;-)

(Local) Adjoint-based Error Estimate

- Adjoint-based error estimates coupled to SOLAR
- Manually performed for the DPW4 meshes
- “V4”: Error estimate based on the artificial viscosities k_2 and k_4
- Only field cells with sensor $V_4 > 5e-07$ are plotted in color

→ See last/third exercise/file: [/3_DPW4_para/](#)





The End

